Reputation effects in the market of certifiers: evidence from the audit industry

Áron Tóth*
University of Bath

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Abstract

Certifiers verify unobserved product characteristics for buyers and thereby alleviate informational asymmetries and facilitate trade. When sellers pay for the certification, however, certifiers can be tempted to bias their opinion to favour sellers. Indeed, accounting scandals and inflated credit ratings suggest sellers may prefer to select dishonest certifiers. I test this proposition by estimating the effect of adverse quality signals on audit demand. Exploiting the natural experiment of Arthur Andersen's demise, I find that auditors with worse quality signals experience a fall in demand. This suggests that reputation effects are at work even in the presence of conflicts of interest.

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1 Introduction

Asymmetric information between seller and buyer can impede mutually beneficial transactions. One of the solutions to this problem is to recruit an independent third party - a certifier - who verifies unobserved product characteristics for the buyer. The certifier's independence is at the heart of the tripartite arrangement. This independence, however, can be compromised when sellers pay for the certification. For instance, in the market of auditors and credit rating agencies (CRA) it is not the investor (i.e. the buyer of the security) who pays for the certifier's services, but the company which is to be impartially rated or audited. In this business model, companies can naturally manipulate their ratings/audits. Furthermore, investors only have a limited power to weed out dishonest certifiers simply because companies, instead of investors, choose auditors and CRA. Ultimately, these problems can pervert the certifier's mission to serve the investing community (Dranove and Jin 2010).

Not surprisingly, this conflict of interest has often been cited as a cause for accounting scandals and, more recently, for inflated credit ratings (e.g. Economist 2004, 2006, BIS-CFGS 2008). Auditors and CRA alike refute the criticism of their business model, arguing that the threat of losing their reputation is a sufficient disciplinary device (e.g. Economist 2005).[1] However, this claim has not yet been empirically substantiated.

A successful mechanism of reputation has three components in the presence of conflicts of interest. Consider the audit market.[2] First, investors have to punish companies which chose low quality auditors. There is evidence that capital markets severely penalise companies whose audit reports are of dubious quality (e.g. Chaney and Philipich 2002, GAO 2003a, Pacini and Hillison 2003, Krishnamurthy et al 2006). Second, this negative capital market reaction should feed into companies' auditor choice, i.e. companies should choose high quality auditors. Third, auditors then should have the incentive to provide high quality audits. The second stage of

[1] An alternative business model where investors would pay for audits and ratings is difficult to implement in practice because free-riding among investors would naturally arise due to easy dissemination of audit reports and ratings.

[2] Mathis et al (2009), for instance, show how reputation can fail to discipline the CRA. There are plenty of anecdotes of 'rating shopping' in the CRA market, but the empirical evidence is scarce and mostly circumstantial (see e.g. Cantor and Packer 1997, Bongaerts et al 2012, Stanton and Wallace 2010).

this mechanism has not been empirically validated yet. In particular, it has not been analysed whether the adverse capital market reaction to low audit quality feeds into companies' auditor choice and if it does, how. A positive effect of adverse quality signals on audit demand means that firms prefer to engage lenient auditors in order to receive favourable reports, suggesting that conflicts of interest overwhelm reputation concerns and clearly fail the disciplinary mechanism. A negative effect, on the other hand, indicates that while investors do not pay for audit services, they can exert discipline on auditors indirectly by forcing public companies to choose high quality auditors – a success of reputation.

In this paper, I exploit the natural experiment of Arthur Andersen's collapse and test the effects of audit quality signals on companies' auditor choice in discrete choice models. The quality signals in this study are auditors' industry specific financial restatement histories, i.e. the proportion of clients in an industry which restated financial statements in the past. I find that auditors' restatement histories are a crucial driving force in the subsequent auditor choice of deserting Andersen clients.

There are compelling reasons why auditors' financial restatement histories should forcibly feed into a company's auditor choice. Restatements are material corrections of published financial statements which cannot be relied upon anymore and have to be reissued. Since the very role of the independent auditor is to ensure that financial statements are fairly presented in all material respects, it appears natural to think that the auditor has not done its job properly if a financial statement has to be restated later. Indeed, there is ample evidence that capital markets receive restatements badly. Before Andersen's collapse, restatements hit the restating company hard: on average, they triggered a 10% fall in the company's market value between 1997 - 2002 (GAO 2003a). Therefore, companies should care about auditors' restatement profiles if only because capital markets do. Furthermore, the Security and Exchange Commission (SEC) considers every restatement to be outright audit failure (GAO 2003a).[3]

The demise of Arthur Andersen provides a particularly well suited laboratory to test the

[3] On the other hand, it is not quite clear to what extent the auditor is responsible for a restatement and as a consequence in the academic literature financial restatements are often thought to be noisy indicators of audit quality, if they are indicators at all (Francis 2004).

importance of quality signals in consumer choice for a number of reasons. First, in empirical analyses of the effects of accreditation, endogenous sample selection is a fundamental problem because the choice of accreditation is most often endogenous (Dranove and Jin 2010). Similarly, circumstances which trigger auditor switch most probably also affect the choice of the succeeding auditor. By focusing on a forced auditor change, however, this sample selection problem is not an issue in the current empirical investigation. Second, customers in this market are firms rather than individuals, therefore it is more likely that we should find a strong notion of rationality at work. Third, Andersen was one of the big 5 auditors. Therefore, simply choosing one of the remaining big 4 auditors could have appeared insufficient to signal integrity to investors. Perhaps not surprisingly there were widespread rumours at the time that Arthur Andersen would not be the only one, but merely the first one to fail (Economist, 2003a,b). It seems reasonable then to expect that former Andersen clients paid distinct attention to quality indicators that could potentially differentiate within the exclusive group of big 4 auditors.[4]

The paper is organized as follows. I review the related literature in Section 2. I describe the estimation procedure in Section 3 and the data in in Section 4. In Section 5, the estimation results are presented. Section 6 discusses robustness and I conclude in Section 7.

2 Related literature

Conflict of interest is a potentially serious problem. For instance, Hubbard (1998) found that privately owned emission inspection facilities in California are markedly more lenient in their passing behaviour than state facilities because, as Hubbard (2002) showed, customers were more likely to return to inspection stations that have previously passed them. Price et al (2012) argue that NBA referees favour home teams, teams losing during games, and teams losing in playoff

[4] The determinants of audit quality (proxied by litigation, SEC enforcement actions, restatements, earnings quality, going-concern/client failure, etc) have been investigated at the client level (e.g. independence of board of directors, tenure of engagement, engagement hours worked), the accounting firm level (firm size, office size, industry experience, etc), the market level (competition, market concentration), and at the level of institutional and legal environment (e.g. legal protection of investors, auditors' legal liability, litigation costs). See Francis (2004, 2011) for comprehensive surveys. This literature, however, has not yet analysed how audit quality affects clients' choice of auditor.

series in order to increase consumer demand. Poitras and Sutter (2002) shows that mandatory safety inspection of cars fails to reduce accidents because of policy impotence. Their econometric analysis suggests that evasion of inspection requirements is the likely cause of ineffective policy as both drivers and garages can mutually benefit from conducting pro forma inspections. Lastly, teachers and students alike have an incentive to inflate test scores, especially when short term gains from gaming the rules are higher and the probability of detection is lower (see Jacob and Levitt 2003 and the references therein).

Quality disclosure often fails to affect demand if ratings are difficult to understand (see Dranove and Jin 2010). Indeed, while the disciplinary force of consumer choice is well established when unobserved quality becomes observable due to some information disclosure (e.g. Foreman and Shea 1999, Mathios 2000, Jin and Leslie 2003, Freedman et al 2012), previous literature often does not find empirical support for imperfect quality signals affecting consumer choice (e.g. Borenstein and Zimmerman 1988, Hodgkin 1996, Mocan 2007, Brown et al 2012).[5] This suggests customers have a difficulty (or find it too costly) to decipher these signals. However, empirical studies on the effects of quality signals on demand have only analysed markets where customers are individuals. The question naturally arises then whether the mechanism of reputation based on imperfect signals works better when customers are firms. In the audit market, audit quality is never directly observed and companies need to rely on imperfect quality signals when choosing among auditors.

The literature on auditor change is vast (see e.g. Francis and Wilson 1988; Landsman et al 2009; Guedhami et al 2009 and the references therein). Most of these articles, however, focus on the selection between big N and non-big N auditors and estimate choice as a function of client attributes. I analyse auditor choice within the group of big N auditors too and also control for auditor characteristics.[6] There are several studies in addition analysing the forced auditor change of Andersen clients. For instance, Barton (2005) and Chen and Zhou (2007)

[5]There is a large literature on advertising as a signal of unobserved quality. However, empirical studies "do not offer strong support for the hypothesis of a systematic positive relationship between advertising and product quality" (Bagwell 2007, pp. 1784)

[6]The big 4 auditors are PricewaterhouseCoopers (PWC), Ernst&Young (EY), Deloitte&Touche (DT) and KPMG. These four auditors and Arthur Andersen constituted the big 5 before 31 August 2002.

examine the timing of client defections. Blouin et al (2007) and Kohlbeck et al (2008) analyse the relationship between client migration and the big 4 auditors' strategies of Andersen office purchases. However, none of these studies investigate how signals of audit quality affected companies' auditor choice. I control for auditor (as well as client) attributes and thereby can test for reputation effects in auditor choice.

3 Econometric model and estimation

In discrete choice models, I investigate how former Andersen clients choose their new public accountant. In particular, I model auditor choice as a function of auditor and client characteristics and test whether the signal of audit quality played a significant role in companies' auditor choice. The quality indicator in this study is the auditor's financial restatement history, i.e. the proportion of clients who restated financial statements in an industry in the past.[7] In the choice models, I will have five choices: one for each big 4 auditor (PWC, EY, Deloitte, KPMG), and one for all the non-big 4 auditors together (NonBig). Unfortunately, I cannot further refine the choice set due to the small number (13%) of companies which chose non-big 4 auditors.

3.1 Econometric framework

I estimate multinomial and nested logit models with auditor and client characteristics.[8] In the multinomial models, company i by choosing auditor j gets utility $U_{ij} = W_{ij} + \varepsilon_{ij}$, where W_{ij} is observable up to some parameters and ε_{ij} is unobserved by the econometrician. Then, company

[7] Financial restatements are, of course, not the only indicators. For instance, auditors' litigation history could also be a straightforward and natural measure. However, the lack of data on litigation constrains the current analysis to financial restatements.

[8] Multinomial logit with alternative characteristics, i.e. the model where choice is a function of both alternative and individual characteristics, is also known as conditional logit with individual characteristics or simply mixed logit (not to be confused with the random coefficient logit).

i chooses auditor j with probability

$$
\begin{aligned}
P_{ij} &= \Pr(W_{ij} + \varepsilon_{ij} > W_{il} + \varepsilon_{il}) \text{ for } \forall l \neq j \\
&= \frac{e^{W_{ij}}}{\sum_j e^{W_{ij}}}
\end{aligned}
\tag{1}
$$

where the second equality follows from the assumption that ε_{ij} is independently and identically distributed type I extreme value (Gumbel) (Train 2002). The multinomial model is based on the assumption that the error terms are identically and independently distributed (IID).[9] A logit model which allows correlation within a subset of choices (nest) relaxes the IID assumption to some extent. Therefore, in order to allow for more general substitution patterns, I also estimate nested logits.

In the nested logit specifications, both the observable and unobservable components of the utility can be broken down into two parts: $U_{ij} = W_{ij} + \varepsilon_{ij} = (V_{iB} + V_{ij|B}) + (v_{iB} + v_{ij|B})$, where V_{iB} depends only on variables that describe nest B and $V_{ij|B}$ on the variables that describe alternative j in nest B, v_{iB} is the unobserved (stochastic) variation across the nests and $v_{ij|B}$ is the random variation within the nest. Note that the presence of v_{iB} induces correlation across the errors within the nest relaxing the assumption of IID errors.[10] However, across the nests errors are assumed to be independent. Then the choice probabilities in a standard nested logit can be expressed as

$$
\begin{aligned}
P_{ij} &= P_{iB} \cdot P_{ij|B} \\
&= \frac{e^{V_{iB} + \frac{1}{\lambda_B} I_{iB}}}{\sum_B e^{V_{iB} + \frac{1}{\lambda_B} I_{iB}}} \cdot \frac{e^{\lambda_B V_{ij|B}}}{\sum_B e^{\lambda_B V_{ij|B}}} \qquad \text{where} \\
I_{iB} &= \ln \sum_{j \in B} e^{\lambda_B V_{ij|B}}
\end{aligned}
\tag{2}
$$

[9] This assumption has a behavioural association with the well known property of Independence of Irrelevant Alternatives (IIA). The IID (IIA) assumption in most applications is too strong since there might be factors affecting the choice that are not specified in the model and hence can induce correlation in the error terms if these unobserved characteristics share some common components across observations.

[10] v_{iB} has a special distribution such that when $v_{ij|B}$ is extreme value distributed so is the total stochastic component $\varepsilon_{ij} = v_{iB} + v_{ij|B}$. See e.g. Berry (1994) or Cardell (1997) for more details.

where $P_{ij|B}$ is the conditional probability of choosing alternative i given that an alternative in nest B is chosen, and P_{iB} is the marginal probability of choosing an alternative in nest B. The parameter λ_B is a measure of the degree of independence in unobserved utility among the alternatives in nest B. I_{iB} is the Inclusive Value or Logsum, the expected utility of choosing an alternative in nest B.[11] The nested logit model is estimated with two nests, one for big 4 (Big) and one for non-big 4 auditors (NonBig).[12] The NonBig nest contains only one alternative (i.e. all the non-big 4 auditors is a single alternative), hence it is degenerate. Note that I am unable to further refine the choice set given the small number of companies which chose non-big 4 auditors. The nested logit model is estimated sequentially.[13] It is often not obvious which variables should enter the lower and which ones the upper level of the nest structure. The way I proceed is as follows. First, I estimate a model with all client characteristics entering at the lower level and having a big 4 accountant as a base category. In this way, I can identify variables which have potential variation across nests but not within the Big nest. I add these variables to the upper level step-wise and hence identify the nest-specific variables.

In order to estimate the auditor choice models, first I need to estimate audit fees. I have data only on the audit fee that a company paid to its newly engaged auditor, but I don't observe the audit fees that the company would have paid to other auditors. Therefore, audit fees must be estimated first. To address the possible endogeneity of prices (e.g. simultaneity bias), I instrument audit fees by a dummy (DEC) which switches on if the company's financial year ends in December (see next section). The estimation of audit fees proceeds as follows. First I regress audit fees on different client characteristics including the instrument over the whole

[11] In other words, it is a weighted average of the utilities associated with the alternatives within the nest, where the weights are probabilities of choosing each alternative.

[12] In many empirical analyses, the nests are not obvious a priori and, therefore, an elaborate range of experiments is often necessary to identify the nest structure that best describes the data (Koppelman and Bhat 2006). However, in the current context the industry configuration of big 4 versus non-big 4 auditors clearly lends itself to a natural partition of the choice set. Therefore, I do not dwell on exploring different nesting structures.

[13] P_{iB} and $P_{ij|B}$ correspond to two logit models, one for the upper ("choice between nests") and one for the lower level ("choice within nest"). The two logit models can be estimated separately (Limited Information Maximum Likelihood, LIML) or jointly (Full Information Maximum Likelihood, FIML). Although FIML is more efficient, the numerical maximisation is much more complicated due to the fact that the joint maximum likelihood function is not globally concave. Since I bootstrap the results, the FIML is computationally expensive and hence the nested logit models are estimated sequentially.

sample and identify the model that best describes the relationship. Then this model is estimated separately on the five subsamples, which correspond to the five alternatives of the choice set. That is, one regression is run on the sample of companies which chose PWC, then another one on EY clients, etc. These five estimated equations are the pricing equations. Calculating the fitted values of these pricing equations for every company in the whole sample, I generate five audit fees (one for each alternative) for each company.[14] These audit fees along with other variables enter the second stage choice models as a regressor, which results in consistent estimates (Pagan 1986, Wooldridge 2010).

Since I have generated regressors and I also correct for the endogeneity of audit fees, the standard errors are, of course, incorrect in the second stage. Therefore, I use nonparametric bootstrapped standard errors with 1000 replications in all choice models where audit fees enter as a regressor. The bootstrap procedure applied is as follows. In each simulation, I take a bootstrap sample from each client set that chose a particular auditor and using these samples I estimate the audit fee regressions for each auditor (pricing equations). Using these regressions, I generate audit fees for all clients in the whole sample. Then I take a bootstrap sample from the whole sample and run the choice model. This procedure is repeated 1000 times. Since audit fees get regenerated in each simulation step, the first stage variation feeds into the second stage resulting in asymptotically correct standard errors.

3.2 Identification

In all choice models in this study, identification relies on an exclusion restriction which takes the form of an instrument affecting audit fees but not auditor choice. The instrument DEC dummy takes the value one if the company's financial year ends in December and zero otherwise. Financial year end affects audit fees because of the auditor's uneven workload during the year. In particular, for about two-third of companies (both in my sample and in the population) the

[14]In addition to client characteristics, auditor and auditor specific industry effects are also controlled for when generating audit fees as the estimates of the intercepts and industry dummies vary across the five pricing equations. Note also that running separate regressions on the five subsamples ensures that the contribution of the instrument to the predicted fee differs across the five choices.

financial year ends in December putting auditors under strong pressure in the period of January - March, while other months of the year are less busy. Therefore, if a company requires audit out of “rush months”, it gets a discount.

However, the end of financial year is clearly exogenous to the choice.[15] In other words, when exactly during the year the company requires an audit does not affect directly which auditor the company chooses; there is only an indirect effect through audit fees. It is hard to imagine a direct causal relationship between choice and the end of the company’s financial year, which would render the instrument invalid. In principle, in the presence of binding capacity constraint an auditor might be unable to take on a client which would further strain its busy period, while it could easily accommodate a company with a financial year ending, say, in June.[16] Four observations work against this argument. First, binding capacity constraints in general apply only in the short run. The audit technology is predominantly labour intensive and therefore capacity can in principle be flexible even in the short run. Second, most of the clients switched from Andersen in the first half of the year leaving enough time for auditors to adjust their capacity for the next "audit peak" in the following year if they needed to.[17] Three, while the demand for the services of the remaining auditors increased considerably due to Andersen’s failure, the supply of auditors also rose due to staff leaving the collapsing audit firm. These three arguments suggest that factor (labour) demand was not completely inelastic: a (possibly unusually high) wage existed at which accounting talent can be hired and, therefore, so did a (possibly unusually high) audit fee at which a client can be accepted regardless of her financial

[15] Most new businesses can choose their financial year end (unless the business is taxed as a sole proprietorship). However, once the corporation’s first tax returns have been submitted to Internal Revenue Services (IRS), it is quite difficult to change the end of the financial year: any change requires the prior agreement of the IRS and an important business reason is usually needed for approval. Furthermore, states often have further rules that the company has to comply with (e.g. in Colorado fiscal year end can be changed only once in every ten years). The choice of financial year can depend on many factors, of which the most important are as follows: when the company is incorporated, the company’s business cycle, whether the company is a subsidiary, and the applicable tax environment.

[16] Note that this argument would also defeat the whole modelling concept since it is assumed that companies choose auditors and not vica versa.

[17] One may object saying trying to re-establish the integrity of their financials, some companies required an immediate audit on previous years’ financial statements. Note that, however, since most of the auditor changes took place in the first half of the year, an immediate audit meant for the auditor "work out of rush months" implying unlikely capacity problems.

year end. That is, there was an audit fee at which any auditor would have been willing and able to expand capacity implying that the end of financial year affects choice only through audit fees. Lastly, note that indeed each big 4 auditor and also non-big 4 auditors engaged Andersen clients of both types (i.e. companies with financial year ending in December and in other months) which again suggests against the idea of binding capacity constraints. Therefore, I regard my instrument as strongly exogenous.[18]

4 Data

Data on audit fees and information on the new auditors of former Andersen clients come from AuditAnalytics, while company balance sheet and income statement items are collected from both Compustat and AuditAnalytics. The sample consists of a cross section of 978 US public companies which switched from Arthur Andersen between October 1, 2001 and August 31, 2002.[19]

Auditor characteristics are controlled for along three dimensions: the auditor's restatement history (quality signal), industry experience and audit fees. The audit quality signal is the auditor's *restatement history* (REST), which is measured by the proportion of clients which restated financial statements in the previous two years in a given industry.[20] Financial restatements are material corrections of published financial statements which cannot be relied upon anymore and have to be reissued. The data contain all restatements as AuditAnalytics didn't record most restatement features.[21] An auditor's *industry experience* (INDEXP) is measured by the total

[18] I allow the impact of the instrument to vary with another variable by interacting DEC dummy with Assets. The joint F statistic of the DEC dummy and the interaction term in the regressions that I eventually use to generate audit fees marginally passes 10, the commonly used cut off value of weak instruments.

[19] I take October 1, 2001 as the start date of the accounting (Enron) scandal, in line with the study of the US Government Accountability Office (GAO) (GAO 2003b). Arthur Andersen surrendered its licenses on August 31, 2002.

[20] Supposedly, clients pay less attention to the overall restatement history of the auditor, they are more concerned about auditor performance in their own industry. This seems an innocuous and intuitive assumption. There was no statistics published on restatements prior to Andersen's demise. However, individual restatements were announced in the media, so a company which follows industry news closely can form an opinion of the industry specific restatement profiles of auditors. Note that AuditAnalytics data didn't allow me to calculate longer restatement history than two years.

[21] GAO has an alternative database on restatements (GAO 2003a). However, this database didn't allow me to identify the industries of restating companies, hence REST could only vary with auditor in this case.

market share (assets) of companies that an auditor audited in a given industry. Thus REST and INDEXP vary with auditor and industry.[22] As mentioned before, *audit fees* (FEES) are estimated as a function of client characteristics. FEES varies with auditor and client.

In addition, I control for a wide range of client characteristics through four dimensions: size, complexity, profitability and risk. These measures are based on balance sheet and income statement data and come from both AuditAnalytics and Compustat. For the summary statistics of client and auditor characteristics, see Table 1 and 2.

(Table 1 and 2 about here)

5 Results

First, I discuss the results of the first stage estimations, the audit fee regressions. Next, I present multinomial and nested logit estimations where choice is a function of both auditor and client characteristics. In the choice models, where the models are run on the whole sample, the five alternatives are PWC, EY, Deloitte, KPMG and NonBig, the latter being non-big 4 public accountants as a fifth single alternative.[23] In the nested logit framework I explicitly make the distinction between the two groups of big 4 and non-big 4 auditors.

Consequently, it would be perfectly correlated with auditor fixed effects in multinomial and nested logit models. In conditional logit settings the GAO and the AuditAnalytics data yielded qualitatively same results (see Toth 2011).

[22] I estimated conditional logits, where I could compare estimates when REST and INDEXP variables vary only with auditor, with auditor and industry, and with auditor, industry and time. Furthermore, in models when REST and INDEXP vary only with auditor, I could compare the robustness of my findings with respect to alternative datasets as well as different horizons of restatement histories, i.e. when REST and INDEXP are calculated based on two years restatement history (AuditAnalytics) and when they are calculated based on 5 years history (GAO database) prior to Andersen demise. The qualitative results are identical across all these models (See Toth 2011).

[23] Note that in the current study the set of non-big 4 auditors consists of only a handful of auditors, those that former Andersen clients ended up choosing. Therefore, throughout the study I will refrain from drawing far reaching conclusions regarding the choice between the sets of big and non-big 4 auditors.

5.1 Audit fee regressions

In the first stage, I estimate models of the following general form:

$$\log(FEES_i) = \alpha + \beta_1' \log(Size_i) + \beta_2 Complexity_i + \beta_3' Profitability_i + \beta_4' Risk_i + \theta' Instrument_i + \varepsilon_i$$

The audit fee regressions for all (big 4 and non-big 4) clients can be found in Table 3; the regressions for big 4 clients only are in Table 4. In both tables client characteristics robustly predict auditor fees. In the final models, 74% of the variation in audit fees is explained, a standard figure in the audit fee literature. All the variables have the right signs and most of them are significant at the 1% level consistently across all models. Perhaps surprisingly, both the significance and the magnitude of the parameters appear very similar in the two tables. Model (6) in Table 3 is estimated separately on the five subsamples of clients corresponding to the five alternatives (not reported) and using these pricing equations five audit fees are generated for each company. The summary result of these estimations can be found in the summary statistics in Table 1 under the heading of Auditor Characteristics.

(Table 3 and 4 about here)

5.2 Multinomial and nested logit models

In this section, I estimate multinomial models (1), where

$$\begin{aligned} W_{ij} &= \mu_j + \eta_1 REST_{ij} + \eta_2 INDEXP_{ij} + \eta_3 \overline{\log(FEES_{ij})} \\ &\quad + \delta_{1,j}' Size_i + \delta_{2,j} Complexity_i + \delta_{3,j}' Profitability_i + \delta_{4,j}' Risk_i \end{aligned}$$

and $\overline{\log(FEES_{ij})}$ is a generated regressor from the first stage estimations.[24] I also estimate nested logit specifications (2), where

$$
\begin{aligned}
V_{iB} &= \gamma_1 Assets_i + \gamma_2 Leverage_i + \varphi IV_{iBig} + IV_{iNonBig} \\
V_{ij|B} &= \mu_j + \eta_{1,B} REST_{ij} + \eta_{2,B} INDEXP_{ij} + \eta_{3,B}\overline{\log(FEES_{ij})} \\
&\quad + \delta'_{1,j} Size_i + \delta_{2,j} Complexity_i + \delta'_{3,j} Risk_i + \delta'_{4,j} Profitability_i
\end{aligned}
$$

Note that since the NonBig nest is degenerate, the coefficient of $IV_{iNonBig}$ is one and it's not identified (See e.g. Heiss 2002). As discussed earlier, the nested logit model is estimated sequentially. *Assets* and *Leverage* are nest specific variables and identified in a step-wise procedure (see Section 3). Importantly, all multinomial and nested models are estimated with auditor specific intercepts μ_j, which act as auditor fixed effects in this setting.[25]

See Table 5 for the results. (Client characteristics are not reported; in general, their coefficient estimates are statistically insignificant. See Toth 2011) The main variable of interest REST is robustly and strongly significant across different specifications and samples. The negative sign of REST means that if an auditor's clients restated financial statements more frequently in the past, then it is less likely that a new client will choose the auditor. Furthermore, auditors' industry experience positively and significantly affects choice (as expected) in most models in

[24] Audit fees enter in the discrete choice models logged because audit fees are also logged in the first stage. (See Wooldridge 2010, Chapter 15.7.2) However, the models have also been estimated when audit fees are unlogged in both the first and second stages and also when audit fees are logged in the first and unlogged in the second stage; the main results are completely invariant to this specification issue.

[25] Several studies investigated how big 4 auditors' strategy of purchasing Andersen offices affected clients' auditor choice. Blouin et al (2007) argues clients with smaller agency and bigger switching costs were more likely to migrate with their previous audit team. However, Blouin et al do not distinguish clients which switched before and after an office was purchased; therefore, it is unable to shed light on whether clients followed their former (Andersen) audit team or in fact the audit team followed its clients. Indeed, Kohlbeck et al (2008) find that in their sample the auditor switch decision of 63% of clients was clearly not affected by auditors' office purchase because either clients (42%) switched earlier than the office was purchased or clients (21%) belonged to offices that were never purchased. Furthermore, Kohlbeck et al (2008) also analysed the determinants of the probability of office purchase: they do find evidence that auditors purchased offices to hire Andersen staff in order to ease staffing shortages brought about by Andersen clients which had already switched to them by then. See also Ramnath and Weber (2008). Nevertheless, I control for the potentially different office purchase strategies of auditors (e.g. PWC didn't buy any Andersen offices) and other unobserved factors through auditor fixed effects in the choice models.

Table 5. The audit fee variable is significant in the nested logit model (8) and it has the expected negative sign across all models. Interestingly, model (7) in Table 5 means that there are significant differences in perceived quality within the exclusive group of big 4 auditors. This finding suggests that the usual quality classification in the audit literature (big 4 – high, non-big 4 – low, see e.g. Francis 2004) can be overly simplistic. An interesting finding is that the effect of REST and INDEXP do not differ across the big 4 and non-big 4 dimensions in any of the models of Table 5.

(Table 5 about here)

Next, I investigate whether the sensitivity of audit demand to perceived quality varies with clients' size, risk or profitability in a multinomial setting. With the aid of interaction terms, I break down the effect of the variables into a client-invariant and client-varying components. The main message from Table 6 is that restatements are evaluated very similarly across clients: none of the restatement interaction terms is significant at conventional levels.[26]

(Table 6 about here)

6 Robustness

The results suggest that financial restatement history is a key driving force of auditor choice. However, some caveats are in order.

There is no within industry variation in REST and INDEXP which renders it impossible to control for unobserved industry effects in the choice models. In principle, there should be some time variation in restatement histories due to the fact that Andersen clients dismissed their former auditor at different points of times. However, this variation proved insufficient for

[26]Before bootstrapping some of the interaction terms between REST and size measures (Assets and Market Value) were weakly significant (10%). One may want to blame the inefficient estimation procedure for the lack of client-varying effects.

identification since the vast majority of companies dismissed Andersen between March and June 2002. In other words, the information in the data have been fully exhausted.

While it is very reasonable to assume that unobserved industry effects play a role in the audit fee regressions (hence the inclusion of industry dummies), it is more difficult to argue that there are industry effects in auditor choice that INDEXP and REST variables do not already account for. Nevertheless, one way to account for unobserved industry effects is to recreate REST and INDEXP using a finer industry classification than the industry dummies. Therefore, I recalculate REST and INDEXP (by splitting, for instance, Trade into Retail and Wholesales Trade) and rerun equations (1) and (2) of Table 5 adding the full set of (coarser) industry dummies. The results are equations (3) and (4) in Table 5. Although controlling for unobserved industry effects causes the significance of the variable of interest, REST, to fade slightly, the point estimates are strikingly similar and robustly significant at the five percent level. This reinforces the argument that unobserved industry effects do not confound the results.

7 Conclusion

In this paper, I tested whether the mechanism of reputation was operational in the audit industry following a market debacle and I find that it was. Market crises, therefore, do not necessarily indicate lack of discipline. In fact the analysis suggests that reputation can work even when it is based on noisy quality signals and when the mechanism is tainted by conflicts of interest. The findings have important lessons for not only the audit industry but for the market of credit ratings too. The CRA industry played an instrumental role in the recent financial crisis and the conflict of interest created by the issuer-pays business model has been the prime suspect for its alleged malfunction. Therefore, testing reputation effects in the audit industry, which applies the exact same business model and hence suffers from similar conflicts of interest, should be an informative exercise for the market of credit ratings.

The current study also informs the debate on regulatory policy after market crises. On the one hand, market crises can signal a broken mechanism of reputation: as the popular argument goes, market debacles lay bare the market's inability to prevent corporate malpractice. Indeed, Andersen's collapse and the alleged market failure swiftly led to the Sarbanes-Oxley Act (2002) and the establishment of Public Company Accounting Oversight Board, an auditor watchdog, which were primarily intended to rectify a broken audit market (Economist 2007). On the other hand, market crises can be the very result of reputation at work. Furthermore, they can also lead to an effective disciplinary mechanism where there was none before if markets learn. Therefore, regulation, although popular, may not be the most adequate response to crises if reputation has the potential to discipline. Instead, enhancing this market mechanism can be more promising: e.g. Jin and Leslie (2003) shows that information disclosure can dramatically improve the workings of reputation. Therefore, public collection and disclosure of data on underlying audit and rating quality could go a long way to improving discipline in these markets.

The result that signals of audit quality is a major driving force of companies' auditor choice may not generalise straightforwardly. This study focuses on a somewhat unique time, at the height of accounting scandals and when a major accounting firm was collapsing. This is a time when public companies were particularly concerned with their auditor's accuracy. Therefore, audit quality signals may be less important drivers of auditor choice in normal times. However, there are good reasons to think that Andersen's failure increased the disciplinary effect of reputation in the audit industry. Due to data limitations, this study cannot directly test how important a role the quality signal played before the market crisis. By investigating consumer choice pre- and post crises, future research could explore in-depth the process through which markets learn.

Table 1: **Summary Statistics: auditor characteristics**

	REST	INDEXP	Arthur Andersen Clients			
			Fees, Act.	Fees, Est.	Asset (Bn)	N
PWC	0.055	0.285	751065	580513	2544	119
EY	0.041	0.195	783873	556035	1481	211
Deloitte	0.031	0.177	850840	507440	2665	180
KPMG	0.034	0.160	798614	645523	1488	182
NonBig	0.005	0.005	127995	260171	62	74

Notes: Third column: average audit fee paid by former Andersen clients to their new auditor. Fourth: estimated average fee that an auditor would have received had it engaged all former Andersen clients. Fifth and sixth: average asset and number of former Andersen clients, respectively.

Table 2: **Summary Statistics: client characteristics**

Variable	Obs	Mean	Std. Dev.	Min	Max
Assets (Bn)	978	3259	22535	0	641100
Revenue (Bn)	978	1622	4761	0	47948
Market Value (Bn)	978	1901	8361	0	154112
Inventory (Mn)	942	136	495	0	6286
Business Segments (No of)	849	2.19	1.53	1	9
Loss	978	0.38	0.49	0	1
ROA	956	-0.10	0.52	-5.60	4.06
Current Assets/Total Assets	828	0.47	0.26	0.01	1
Inventory/Revenue	934	0.11	0.29	0	5.65
Quick Ratio	816	2.32	3.97	0.03	66
Goingconcern	978	0.05	0.22	0	1
Leverage	956	0.57	0.33	0.01	3.57
DEC	978	0.72	0.45	0	1
Industry dummies (NAICS code):					
Agriculture	978	0.00	0.05	0	1
Natural Resources	978	0.06	0.24	0	1
Utilities	978	0.05	0.21	0	1
Manufacturing/Construction	978	0.36	0.48	0	1
Trade (Retail, Wholesales)	978	0.07	0.26	0	1
Services	978	0.21	0.41	0	1
Information Technology	978	0.10	0.30	0	1
Financial Sector	978	0.14	0.35	0	1

Notes: Loss: 1 if the company produced loss previous year. Goingconcern: 1 if the company received a 'going concern' audit opinion previous year. DEC: 1 if the company's financial year ends in December.

Table 3: **Audit Fee Regressions, all clients**

	(1)	(2)	(3)	(4)	(5)	(6)
log(Assets)	0.230***	0.207***	0.253***	0.328***	0.329***	0.256***
	(8.25)	(7.57)	(7.48)	(8.49)	(8.55)	(5.88)
log(Revenue)	0.157***	0.201***	0.166***	0.107***	0.102***	0.104***
	(6.70)	(8.57)	(6.68)	(3.59)	(3.43)	(3.51)
log(Market Value)	0.043**	0.060***	0.050***	0.052***	0.063***	0.068***
	(2.57)	(3.62)	(2.85)	(2.94)	(3.52)	(3.82)
log(Inventory)	0.070***	0.065***	0.073***	0.054***	0.047**	0.052***
	(3.73)	(3.59)	(3.74)	(2.66)	(2.31)	(2.59)
Business Segments	0.085***	0.082***	0.085***	0.082***	0.082***	0.082***
	(5.26)	(5.22)	(5.28)	(5.12)	(5.15)	(5.18)
DEC	0.123**	0.106**	0.118**	0.123**	0.119**	-0.350**
	(2.33)	(2.08)	(2.31)	(2.43)	(2.37)	(-2.45)
Loss		0.225***	0.171***	0.165***	0.153***	0.156***
		(4.33)	(3.17)	(3.07)	(2.86)	(2.93)
ROA		-0.195***	-0.188***	-0.161***	-0.127***	-0.137***
		(-4.40)	(-4.29)	(-3.64)	(-2.82)	(-3.05)
Current Assets/Total Assets			0.260**	0.525***	0.557***	0.557***
			(2.29)	(4.08)	(4.34)	(4.37)
Inventory/Revenue				0.173	0.251	0.222
				(0.92)	(1.33)	(1.18)
Quick Ratio				-0.043***	-0.036***	-0.036***
				(-4.83)	(-3.98)	(-4.01)
Goingconcern					0.163	0.150
					(1.45)	(1.35)
Leverage					0.196**	0.166**
					(2.32)	(1.98)
log(Assets) · DEC						0.089***
						(3.50)
Constant	-4.044***	-4.312***	-4.454***	-4.554***	-4.711***	-4.375***
	(-48.07)	(-47.62)	(-34.47)	(-34.08)	(-33.15)	(-25.68)
N	836	836	767	759	759	759
R^2	0.704	0.723	0.731	0.736	0.739	0.743
Adjusted R^2	0.700	0.719	0.727	0.731	0.734	0.738
F Statistics	196	179	158	148	131	126

*Notes: Dependent variable is log(FEES). Regressions are run on the whole sample. Industry dummies included. t-statistics are in parentheses, *** p<0.01, ** p<0.05, * p<0.1.*

Table 4: **Audit Fee regressions, big 4 auditor clients only**

	(1)	(2)	(3)	(4)	(5)	(6)
log(Assets)	0.221***	0.196***	0.246***	0.332***	0.328***	0.237***
	(7.50)	(6.77)	(6.67)	(7.92)	(7.85)	(4.87)
log(Revenue)	0.159***	0.199***	0.167***	0.100***	0.096***	0.099***
	(6.42)	(7.96)	(6.35)	(3.20)	(3.05)	(3.18)
log(Market Value)	0.039**	0.057***	0.050**	0.052***	0.063***	0.072***
	(2.11)	(3.13)	(2.55)	(2.66)	(3.16)	(3.61)
log(Inventory)	0.099***	0.092***	0.097***	0.073***	0.065***	0.075***
	(4.94)	(4.68)	(4.56)	(3.12)	(2.80)	(3.22)
Business Segments	0.084***	0.082***	0.080***	0.077***	0.077***	0.076***
	(4.89)	(4.90)	(4.63)	(4.56)	(4.56)	(4.50)
DEC	0.127**	0.110**	0.114**	0.115**	0.109**	-0.461***
	(2.28)	(2.02)	(2.09)	(2.15)	(2.02)	(-2.72)
Loss		0.219***	0.177***	0.173***	0.162***	0.170***
		(4.02)	(3.12)	(3.06)	(2.85)	(3.01)
ROA		-0.161***	-0.146***	-0.122**	-0.097*	-0.107**
		(-3.25)	(-2.99)	(-2.47)	(-1.94)	(-2.15)
Current Assets/Total Assets			0.258**	0.547***	0.570***	0.565***
			(2.10)	(3.90)	(4.07)	(4.07)
Inventory/Revenue				0.196	0.318	0.249
				(0.67)	(1.08)	(0.85)
Quick Ratio				-0.044***	-0.038***	-0.038***
				(-4.78)	(-4.00)	(-4.07)
Goingconcern					0.078	0.104
					(0.55)	(0.74)
Leverage					0.221**	0.188*
					(2.19)	(1.88)
log(Assets) · DEC						0.103***
						(3.55)
Constant	-4.074***	-4.313***	-4.480***	-4.594***	-4.732***	-4.314***
	(-43.24)	(-42.84)	(-31.36)	(-30.43)	(-29.55)	(-21.82)
N	753	753	693	687	687	687
R^2	0.696	0.712	0.723	0.728	0.730	0.735
Adjusted R^2	0.692	0.707	0.718	0.722	0.724	0.729
F Statistics	170	152	136	128	113	109

*Notes: Dependent variable is log(FEES). Regressions are run on the sample of companies which chose big 4 auditors. Industry dummies included. t-statistics are in parentheses, *** p<0.01, ** p<0.05, * p<0.1.*

Table 5: **Multinomial and Nested Logit**

	ML							NL
	All Clients						Big 4	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
REST	-5.374***	-5.373***	-6.514**	-6.424**	-5.239***	-5.306***	-5.696***	-6.146***
	(-3.49)	(-3.52)	(-1.99)	(-1.98)	(-2.81)	(-2.83)	(-3.32)	(-3.79)
REST · *NonBig*		16.549		110.913		14.271		-1.178
		(0.37)		(0.30)		(0.38)		(-0.02)
INDEXP	1.256**	1.234**	1.395	1.417	1.241**	1.246**	1.230**	1.212**
	(2.43)	(2.39)	(1.36)	(1.38)	(2.33)	(2.34)	(2.31)	(2.32)
INDEXP · *NonBig*		-17.918		1.195		-18.453		-66.215
		(-0.26)		(0.01)		(-0.35)		(-0.74)
$\overline{\text{log(FEES)}}$	-0.337	-0.120	-0.065	0.141			-0.834**	-0.726**
	(-1.12)	(-0.38)	(-0.20)	(0.41)			(-2.38)	(-2.17)
$\overline{\text{log(FEES)}}$ · *NonBig*		-1.467**		-1.336*				-0.846
		(-2.12)		(-1.82)				(-1.10)
Industry Dummies	No	No	Yes	Yes	No	No	No	No
N	759	759	759	759	759	759	687	759
LogLikelihood	-1064	-1059	-1029	-1024	-1064	-1064	-897	-1057

Notes: Dependent variable is auditor choice. Client characteristics included (see Table 2 for the list of variables). $\overline{log(FEES)}$ *is a generated regressor. Non-parametric bootstrapped standard errors with 1000 replications. z-statistics are in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Multinomial logit: First six columns: estimated on the whole sample. Seventh column: estimated on the subsample of companies which chose big 4 auditors. Nested Logit (last column): Nesting structure: Big (PWC, EY, Deloitte, KPMG), NonBig (NonBig). Assets and Leverage enter the upper, all other client characteristics enter the lower level of the nest structure. The model is estimated sequentially (LIML). The LogLikelihood value is the sum of the loglikelihoods of the upper and lower levels.*

Table 6: **Multinomial logit with auditor and client characteristics interacted, all clients**

	$X =$					
	Assets	Revenue	Market Value	Inventory	Business Segments	Loss
REST	-2.660	-4.012**	-4.015**	-5.580***	-3.760	-5.518***
	(-1.40)	(-2.10)	(-2.40)	(-2.92)	(-1.40)	(-2.85)
REST $\cdot X$	-0.001	-0.001	-0.001	0.005	-0.541	2.600
	(-1.56)	(-0.81)	(-1.20)	(0.37)	(-0.69)	(0.60)
INDEXP	1.264**	1.204**	1.025*	0.807	0.820	1.679**
	(2.12)	(1.99)	(1.80)	(1.29)	(0.89)	(2.55)
INDEXP $\cdot X$	0.000	0.000	0.000	0.004	0.162	-1.395
	(0.01)	(0.04)	(0.46)	(1.06)	(0.54)	(-1.25)
$\overline{\text{log(FEES)}}$	-0.344	-0.386	-0.418	-0.370	-0.482	-0.892**
	(-1.17)	(-1.30)	(-1.38)	(-1.24)	(-1.21)	(-2.44)
$\overline{\text{log(FEES)}} \cdot X$	0.000	0.000	0.000*	0.001	0.077	1.025**
	(0.17)	(0.59)	(1.69)	(0.53)	(0.52)	(2.53)
N	759	759	759	759	759	759
LogLikelihood	-1061	-1062	-1057	-1061	-1063	-1060

	$X =$					
	ROA	Current Assets/ Total Assets	Inventory/ Revenue	Quick Ratio	Goingconcern	Leverage
REST	-5.135***	-7.094**	-5.342**	-3.634*	-5.619***	-6.544
	(-2.99)	(-2.42)	(-2.45)	(-1.70)	(-3.24)	(-0.95)
REST $\cdot X$	-5.960	9.228	-1.107	-1.536	16.346	1.778
	(-0.68)	(1.19)	(-0.04)	(-1.14)	(0.74)	(0.18)
INDEXP	1.383**	2.564***	0.760	1.038	1.239**	1.578
	(2.55)	(2.91)	(1.15)	(1.47)	(2.34)	(1.22)
INDEXP $\cdot X$	2.158	-3.670*	7.264	0.178	-0.175	-0.531
	(1.46)	(-1.86)	(1.24)	(0.57)	(-0.05)	(-0.28)
$\overline{\text{log(FEES)}}$	-0.389	-1.424***	-0.361	-0.465	-0.419	-0.237
	(-1.27)	(-2.85)	(-1.12)	(-1.43)	(-1.34)	(-0.58)
$\overline{\text{log(FEES)}} \cdot X$	-0.172	2.263***	-0.051	0.067	0.895	-0.178
	(-0.53)	(2.99)	(-0.03)	(1.28)	(1.22)	(-0.35)
N	759	759	759	759	759	759
LogLikelihood	-1062	-1058	-1063	-1062	-1062	-1063

Notes: Dependent variable is auditor choice. The heading of a column indicates the variable which auditor characteristics are interacted with. Client characteristics included (see Table 2 for the list of variables). $\overline{log(FEES)}$ *is a generated regressor. Non-parametric bootstrapped standard errors with 1000 replications. z statistics are in parentheses, *** p<0.01, ** p<0.05, * p<0.1.*

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